fMRI clustering based on connectivity profiles

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Context

Data clustering in fMRI is a way to deal with the issues of data normalization and inter-patients comparisons, and to find an adequate structure of the data. New methodologies have recently emerged to address this question in the domain of functional MRI data processing and analysis. A key point of these methods is to determine the metric on which the clustering is based, in order to obtain regions both spatially compact and functionally homogeneous, regarding functional connectivity.

The first parcellation methods proposed were purely anatomic and lacked of anatomo-functional coherence. The anatomo-functional parcellations methods are most of the time based on the locations of the functional activations. A main limitation of these methods is the dependence on a priori information, like seeds regions of reference [1] or regressors [2] and [3], where different choices may lead to different clusters. These methods are therefore reference or paradigm dependant.

Another aspect that must be addressed is the homogeneity of the clustering regarding neural activity. The noise of the signal induces a spatial correlation in fMRI data that must be taken into account. If the functional metric is only based on the correlation of the signals, it is difficult to determine if a significant correlation between two neighbor voxels is due to neural connectivity or to the local correlation of noise. To separate functional connectivity and correlation due to noise, there must be a certain distance between two voxels [4].

We present a new clustering method that considers this distance in the functional dimension of its metric, and that allows merging of voxels in spatially and functionally homogeneous clusters without specifying a priori information on the data.

Methodology

Our method is based on the one proposed by Thirion *et al.* [2]. We first determine a graph that represents the spatial neighborhood relationships of the voxels. This graph is then functionally weighted. For this purpose, we introduce a new spatio-functional metric, which is based on the data, to determine spatially and functionally homogeneous clusters.

We define the connectivity profile, based on the notion of connectivity map [5]. The profile is defined for each voxels. It corresponds to a vector of correlation coefficients, relating the voxel to every other voxel in the brain. The profile allows addressing the problem of spatial correlation. Actually, the spatial correlation due to the noise alters only the neighbors of the voxel, which represents a small part of the connectivity profile.

The weighting of the neighborhood graph is defined by the Euclidean distance between the profiles of connectivity. Dijkstra's shortest path method applied on the resulting graph allows us to construct a distance matrix between the voxels in a new spatio-functional space with a new topology (Figure 1). At last, a C-means clustering is performed to merge the data into distinct regions (Figure 2). Our method leads to compact and homogenous clusters (Figure 3).

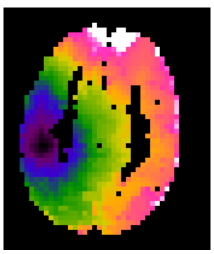

Figure 1: Topology of a voxel showing spatio-functionally compact region.

Figure 2: Example of 500-clustering data

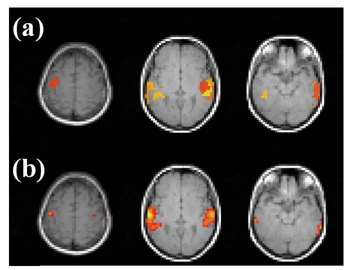

Figure 3: (a) activation map of clustered audio data (pcorrected<0,05), (b) activation map of the original audio data (pcorrected<0,05)

Conclusion:

The method we introduced here offers two major advantages in comparison with the classical clustering method: it allows dealing with the problem of spatial correlation of noise that can lead to bad mergings in functional domain and it allows defining a new functional dimension exclusively based on the data without taking the paradigm into account trough specified regressors. The resulting clusters form a partition of the data in homogeneous regions according to both spatial and functional connectivity points of view.

References :

[1] – Flandin G, Kherif F, Pennec X, Riviere D, Ayache N, Poline J.B : Parcellation of Brain Images with Anatomical and Functional Constraints for fmri Data Analysis IEEE International Symposium on Biomedical Imaging (2002)

[2] - Thirion B,Flandin G, Pinel P, Roche A, Ciuciu P, Poline J.B : Dealing With the Shortcomings of Spatial Normalization: Multi-Subject Parcellation of fMRI Datasets, Human Brain Mapping 27:678–693 (2006)

[3] – Golland P, Golland Y, Malach R: Detection of Spatial Activation Patterns As Unsupervised Segmentation of fMRI Data To appear in Proc. MICCAI 2007

[4]- Bellec P, Perlbarg V, Jbabdi S, Pélégrini-Issac M, Anton J-L, Doyon J, Benali H: Identification of large-scale networks in the brain using fMRI, NeuroImage 29 :1231 – 1243 (2006)

[5] - Cordes D, Haughton VM, Arfanakis K, Wendt GJ, Turski PA, Moritz CH, Quigley MA, Meyerand ME: Mapping functionally related regions of brain with functional connectivity MR imaging, AJNR Am J Neuroradiol 21:1636–1644 (2000)